Control Strategies for Soft Robotic Manipulators: A Survey

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Abstract: With the rise of soft robotics technology and applications there have been increasing interests in the development of controllers appropriate for their particular design. Being fundamentally different from traditional rigid robots, there is still not a unified framework for the design, analysis and control of these high dimensional robots. This review paper attempts to provide an insight into various controllers developed for continuum/soft robots as a guideline for future applications in the soft robotics field. A comprehensive assessment of various control strategies and an insight into the future areas of research in this field is presented.

1. INTRODUCTION

Biological organisms exploit softness of the body for compliance to reduce the complexity in interacting with the environment. This characteristic is promising to advance robotic systems to operate robustly and adaptively in unstructured environments. Incorporating softness in robotic systems, in particular robotic manipulators which is the focus of this article, is studied under the domain of 'soft robotics'. This term is associated with two distinct design approaches: (i) compliant joints (active or passive) within rigid-link robots [70, 1]; (ii) continuum robotic manipulators [2]. The discussion in this article is restricted to the latter one.

Although the field of continuum robotic manipulators was founded in the 1960s, a formal research on the design and control can be dated back to the early 1990s. These systems are the result of the evolution of manipulator design from discrete mechanisms constructed from a series of rigid-links to mechanisms without rigid-links but rather with elastic structures capable of continuous bending along their length (depicted in Fig 1). A novel sub-domain of continuum manipulators, referred to as 'soft robotic manipulators' [3,4], has been rapidly growing in the past decade since roboticists found inspiration in boneless biological organisms such as octopus arms which are able to exploit the 'mechanically intelligent' arrangement of just their muscles to exhibit dexterous advanced manipulation capabilities in cluttered environments. This has been translated into new range of continuum manipulators made up of soft materials such as silicone due to their ability to undergo a large deformation under normal operation. The underlying idea is to use principles of embodied intelligence [77] and morphological computation [78] to exploit the soft material properties to enable machines with properties such as inherent compliance, variable stiffness, and highly dexterous motion in unstructured environment. The resulting systems have the ability to simplify a wide range of well-known complex tasks. Additionally, they offer a low-cost alternative to numerous robotic applications [4]. Furthermore, the deformability of the soft material offers compliance which facilitates safe human-robot interaction in comparison to their rigid counterparts. These desirable characteristics are the fundamental reason behind their rapidly increasing demand in industrial, surgical, and assistive applications.

However, the long term success for the practical application of these systems is dependent upon the development of real-time kinematic and/or dynamic controllers that facilitate fast, reliable, accurate, and energy-efficient control. This is non-trivial because: (i) unlike rigid manipulators, the movement of which can be specified by three translations and three rotations, elastic deformation of soft robotic manipulators results in virtually infinite degrees-of-freedom (DoF) motions, (bending, extension, contraction, torsion, buckling, etc.) (ii) the material properties exhibit non-linear characteristics such as compliance and hysteresis that restricts high-frequency control (iii) the wide range of design and actuation techniques which makes each of these robots have unique properties (Refer to [5] for a detailed review on design and actuation technologies for soft robots). However, as this is an active field of research still in its infancy, the fundamental purpose of this survey is to provide an in depth assessment of various control strategies established within the domain of continuum robotic manipulators, in the past decade, with the aim to segue into a guide for researchers towards possible directions for developing controllers for soft robotic manipulators.

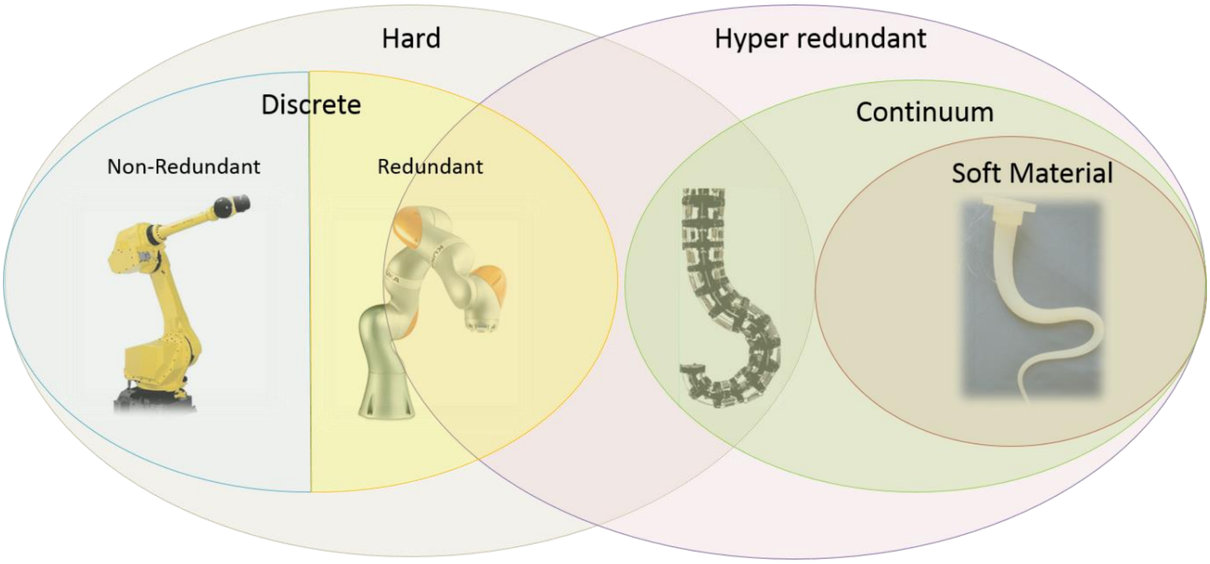

FIG. 1. Evolution of rigid-link manipulators based on discrete mechanisms to bio-inspired continuum robotic manipulators based on structures capable of continuous bending, studied in detail in[3].

Comprehensive reviews of control strategies for continuum robotic manipulators [6, 7, 2, 8, 9] are primarily focused on design, fabrication, modelling, and sensing. However, there is no in-depth analysis of the control approaches that have emerged over the years. Furthermore, they lack focus on the recent development of controllers via model-free approaches. This survey tries to firstly enumerate all such developments in this field in the past decade; secondly, it aims to provide a unified overview of key terminologies, advantages, and drawbacks of these controllers; finally, we aim to summarize these concepts in a table which, in addition to a systematic review, also provides the readers an overview into the chronological developments that have led to the current landscape and future prospects of development in this domain. As the focus of this paper is restricted to controllers developed within the domain of continuum manipulators that can be adopted for soft robotic manipulators, the paper does not dwell much into modelling techniques, theoretical studies, wearable robots and concentric tube robots. The role of sensing and variable stiffness actuation for control is also beyond the scope of this paper.

2. PRELIMINARIES

Although a lot of classic terminologies used for rigid robots can be directly adapted to this field, special care must be given to understand the applicability and limitations of these terms. Consequently, we first state key terminologies and their corresponding definitions that will be used throughout the paper to describe the controllers in a unified manner. Next, we lay out the classification schema used to systemically analyse the controllers summarized in Table 1.

2.1 Definitions

Figure 2 provides the definitions and terminologies that we will be referring to throughout the paper. The purpose of the figure is to give the readers an idea of the different levels of mapping involved in the control of a continuum/soft manipulator and its differences from traditional rigid robot control.

Operating Space	Definition	Pneumatic	Tendon-Driven
Actuator Space	$\boldsymbol{q} \in \mathbb{R}^k$	$q \propto Eg: chamber\ pressure\ or\ volume\ or\ both$ $k = number\ of\ actuators$	$q \propto Eg: motor\ position/\ torques$ $k = number\ of\ actuators$
Joint Space	$\varsigma \in \mathbb{R}^l$	$\varsigma \propto Eg: cable - potentiometers/tension$ $l \geq number\ of\ actuators$	$\varsigma \propto Eg: cable\ length/\ tension$ $l \geq number\ of\ actuators$
Configuration Space	$\boldsymbol{\zeta} \in \mathbb{R}^m$	$\zeta \propto no.\ of\ independent\ physical\ parameters\ that\ define\ the\ configuration\ of\ the\ manipulator$ $m = l\ under\ steady - state\ conditions$ *	
Task Space	$\boldsymbol{x} \in \mathbb{R}^n$	$x \propto position\ or\ pose\ or\ forces\ applied\ at\ end - effector$ $n = dimension\ of\ target\ variable$	

*dimensions of uniform and nonuniform manipulators remain the same even under gravitational loading, albeit represented differently
Note: A manipulator is considered redundant when $n \leq l$
Note: In Fig 4 - 9, the operating space has been abbreviated using the first letter of each word. So for eg. Actuator Space is mentioned as A.S.

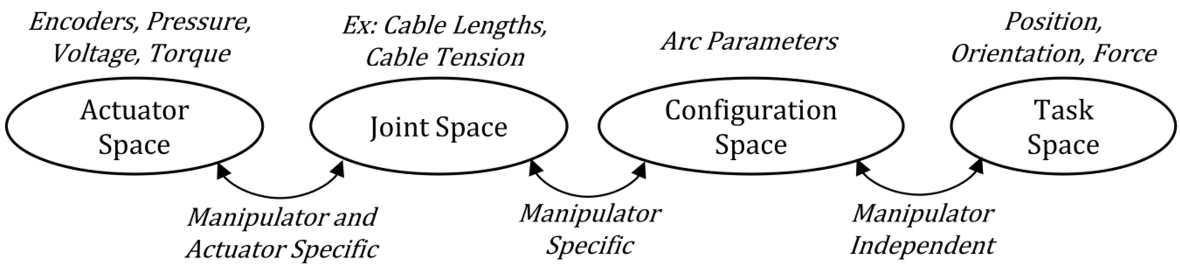

FIG. 2. Operating spaces of a continuum manipulator and their definitions.

2.2 Classification Schema

1. Modelling approach:
    a. Model-based controllers rely on analytical models for deriving the controller.
    b. Model-free controllers use machine learning techniques or empirical methods.
    c. Hybrid controllers combine model based and model free approaches.
2. Design:
    a. Actuation: Tendon-driven, Pneumatic, Interleaved, Simulated platforms.
    b. Actuation details: No. of segments/actuators, arrangement, shape, material
    c. Manipulator details: intended applications

3. Control:
    a. Operating Space:
        i. Low-level: Joint and/or actuator space
        ii. Mid-level: Inverse Static/kinematic[1], dynamic[2]
        iii. High-Level: Path planning[3]
    b. Controller details: tested for planar/non-planar applications, required sensors
    c. Performance: Error Measurements, Theoretical Error Convergence, Stability.

3. Model-Based Static Controllers

Soft robots present a formidable challenge to modelling due to their high dimensionality. Nonetheless, tractable kinematic models can be developed by adopting a steady-state assumption; i.e. under force equilibrium, the full configuration of the soft manipulator can be defined by a low dimensional state space representation. In all the papers that are reviewed this assumption is valid and therefore we interchangeably use the term 'statics' and 'kinematics' even though this is not a common practice in traditional robotics. The simplest and most commonly used kinematic/steady-state model assumes that the configuration space of a three dimensional continuum/soft module can be parametrized by three variables, more commonly referred to as the constant curvature (CC) approximation [10]. It reduces an infinite dimensional structure into just three dimensions, thereby ignoring a large portion of the manipulator dynamics. This has been found to be a very good approximation if: (i) the manipulator is uniform in shape and symmetric in actuation design, (ii) external loading effects are negligible, (iii) and torsional effects are minimal. It is important to realize that the CC model arises due to a constant strain approximation along the length of the manipulator and therefore is a model truly valid only in the steady-state condition [13]. In [11] it was demonstrated that the variations in the kinematic manipulability ellipsoid is very less when going from a low dimension to a high dimension representation of the manipulator configuration. This could explain the relative success of the CC model. For multi-section continuum/soft manipulators, each constant curvature section can be stitched together to provide the Piecewise Constant Curvature (PCC) model [12]. Concurrently, more complex modelling approach using beam theory was pursued using beam theory [13] and cosserat rod theory [14]. However, the improvement in accuracy attained by a more complex was not significant compared to their computational and estimation cost and therefore have been limited in their usage.

Once a kinematic model is established, it is necessary to invert the kinematics to obtain the desired actuator or configuration space variables. This can be pretty straightforward and has been widely studied for rigid manipulators and can be done with differential inverse kinematics [12, 15], by direct inversion [16] or by optimization [17]. Further, a low level controller takes care of tracking in the actuator/joint space, usually using a simple linear closed loop controller. Additionally, actuator compensation techniques might have to be used because of the presence of friction, hysteresis [18] or tendon coupling [19] that can cause deviations from the forward steady-state model.

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[1] Static controllers are time invariant controllers where the control variables are zero order.
[2] Dynamic controllers consider the configuration space and/or task space variables velocities in the control algorithm.
[3] High level controllers which prescribe the reference path in task space are primarily application based. Since the area of soft robotics is still in its incipient phase, a review on high level controllers are beyond the scope of this paper.

The need to model and compensate for slackening, tendon load coupling and tendon path coupling for multi-section manipulators was first addressed in [16]. A numerically estimated static model was used for the forward model and inverse model was obtained by optimization. However, there still lacked an expression for friction effects and the approach was used only for configuration tracking. One of the fundamental modelling difficulties involved with cable driven actuators is the path coupling among sections. For independent actuation methods, only the load coupling needs to be considered. Further on researchers started investigating the importance of sensors for compensating modeling uncertainties without the necessity for formulating very complex compensation techniques [20, 17]. As an extension of [16], a closed loop task space controller was proposed and experimentally validated for the first time in [17] with a 5 DoF per section kinematic model. For this, the inverse kinematics (IK) problem is formulated as a constrained nonlinear optimization problem where the desired joint configuration that reduces the current tracking error is estimated while satisfying the forward kinematic model and cable tension constraints (to avoid slacking). By representing the kinematics in the velocity level, their approach gains leverage in terms of higher accuracy (submillimeter) and robustness to model uncertainties, but would need to solve a high level path planner.. But (Refer Fig.3). The downside of the direct task space controller is instability (can be solved by lower control frequency; 5Hz for [17]) and slower convergence. In [20], a configuration space controller is proposed which uses external sensory information about the configuration and internal sensory information about the joint variables to achieve asymptotic tracking of a stationary configuration target. By providing additional tracking information and framing a cascaded controller they were able to reduce coupling effects and decrease the phase lag while tracking a time varying trajectory. Being a configuration space feedback controller, the control loop was run faster at 150 Hz. Interestingly, significant phase lag was observed even for tasks at 2 Hz and this is highly undesirable at the low level. Similarly in [21], two closed loop controllers in the task space (Fig. 4) and joint space (Fig. 5) was compared. The advantage of a direct closed loop task space controller is that it can provide asymptotic convergence of the error even with model uncertainties. On the other hand, a joint space controller can offer independent control of the joint variables allowing for individual tuning and hence more stability, especially if the joint/actuator motions are discrete. Note that for all the above mentioned controllers there is also a closed loop actuator space controller, usually a servo controller, which is assumed to provide perfect tracking. All these methods rely on the CC approximation for modelling.

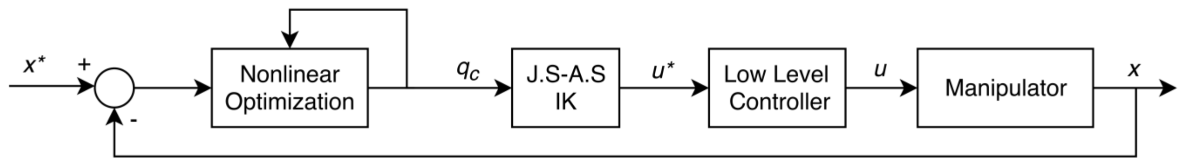

FIG. 3. A closed loop task space controller implementation. A^* represents the desired variable value, A_c represents the commanded variable value.

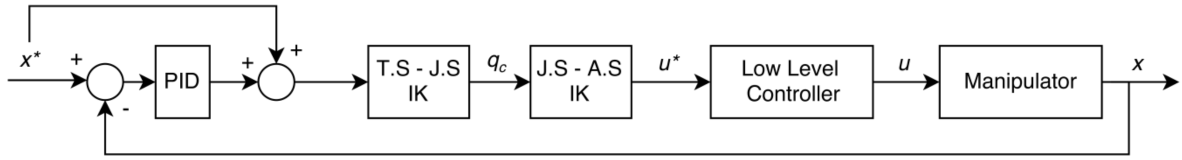

FIG. 4. A closed loop task space controller implementation.

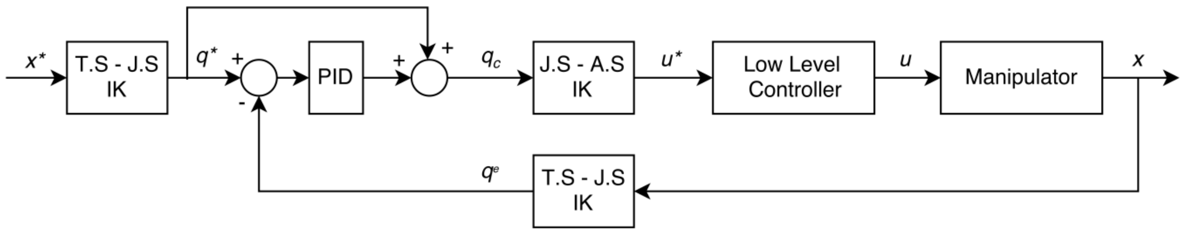

FIG. 5. A task space controller implemented by closed loop control in the joint space. A^e represents the variable estimate.

Following the strong coupling between continuum manipulator's kinematics and static force model, controllers foraying into compliance/force control started to emerge [22, 23, 24]. In [23] it was demonstrated that by knowing the current internal actuation forces and the configuration space variables an estimate of the external generalized forces can be formed. Using the estimate of the external force and the compliance matrix (maps the change in actuator forces to the tip wrenches) a configuration space controller for reducing tip forces for surgical purposes was proposed. As an extension of [23], a hybrid position/force controller in the configuration space was realized in [24] (Fig. 6). Desired twist and wrench vectors are projected orthogonally (for decoupling the control effort into feasible motions) and transformed to configuration space references using differential inverse kinematics and the configuration space compliance matrix (maps the change in configuration space variables to the tip wrenches) respectively. Hybrid position/force control was realized in [22] without the need of force sensors. This was done by numerically calculating the transformation matrix that maps the transformation from the tip of an unloaded continuum manipulator to the tip position when acted on by external forces using cosserat rod theory. With the transformation formulation, the desired joint position that attains a particular end effector force and orientation was estimated using fixed point iteration. Compensating models deviations due to friction and other nonlinear material behavior remains an open research topic.

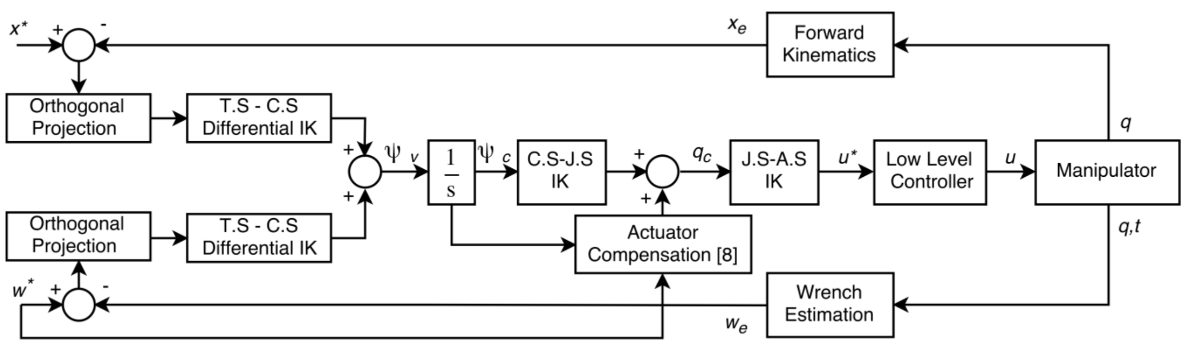

FIG. 6. Closed loop tasks space control of position and force implementation. A_v represents the first order derivative of the variable.

Further on researchers started to focus on more complex kinematic formulations by extending the CC model, mostly due to the rise of biologically-similar tapering continuum robots. The first such method was the use of the Variable Constant Curvature (VCC) approximation which models a single module as *n* segments of constant curvature; where the curvature of each segment depends on the radius of the segment, thus creating a high dimensional configuration space [25, 26, 27]. The VCC model for a three section pneumatically actuated continuum robot, with the procedure for segmentation of the sections, was first elucidated in [26, 27]. A resolved motion rate algorithm was used for the closed loop control of the robot due to the double advantage of redundancy resolution and the robustness it provides to model uncertainties (Fig. 7). Visual servo control of a two dimensional image feature point in three dimensional space using a cable driven soft conical manipulator was proposed using the VCC model in [25]. A differential kinematics based controller, similar to the one in [26], with the control objective of reducing the feature point tracking error was proposed. An adaptive algorithm for depth estimation was also described. Similarly, efficient numerical techniques for solving in real time the complex cosserat models were detailed in [73], however no control experiments were demonstrated.

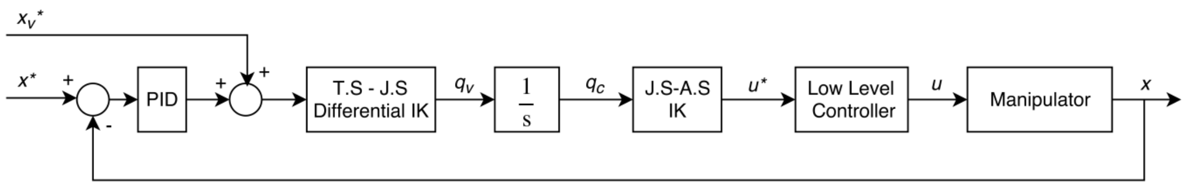

FIG. 7. First order resolved motion rate algorithm for closed loop task space control. Note the similarity to the first implementation in Fig. 3. The additional feedforward component allows for faster convergence.

Contrary to ongoing developments, use of simplified kinematic models for control was proposed in [28]. The idea behind this is that the reduced accuracy due to the inaccurate kinematics can be compensated or even improved with the increased control cycle frequency gained due to the low computational cost. However, the method was validated only on simulations and would not be directly transferable to a real setup at the same frequency without considering the low level dynamics as observed in [20]. On the other spectrum, a numerically exact approach for statics modelling using asynchronous Finite Element Analysis (FEM) was described in [29]. Optimization using quadric programming (QP) algorithm was used to obtain the inverse solution which is used to control the actuators at high frequencies while a low frequency loop FEM simulation feeds the inputs to the QP solver.

Recent developments in terms of model based static controllers are factored on the design aspects. A Closed loop task space controller was applied on an interleaved continuum-rigid manipulator in [30]. The main idea of the approach is to use the well behaved rigid links in tandem with the flexible elements to compensate for the errors obtained while tracking a desired tip position thereby obtaining much lower bound on the tracking error. However, the scalability of such designs for high dimensional systems is still a question mark. Currently the manipulator is designed with the rigid components set up at the base, but it will be tricky to add further components in serial. On the other hand, kinematic control of a pneumatically actuated soft manipulator entirely made from a low durometer elastomer was detailed in [31]. The control architecture is similar to [20] and tries to achieve tracking of configuration space variables using a cascaded PI-PID in the configuration space and actuator space (cylinder displacement, in this case) respectively. The task space to configuration space inverse kinematics is obtained a nonlinear constrained optimization. Both the above mentioned approaches used the CC approximation for the configuration space model.

3.1 Summary of Model-Based Static Controllers

Model-based static controllers are currently the most widely used and studied strategy for control of continuum/soft robots. Majority of the model-based controllers rely on the CC approximation since more complex models are computationally expensive and are design specific. However, with validation of the CC model for a completely soft robot [31] and its wide application for control of many continuum/soft robots it is still one of the most reliable and easily applicable method for static control of uniform, low mass manipulators. More complex methodologies have not achieved exceptional performance improvements because of their computational cost and numerous parameters that have to be estimated. This was also observed in recent comparisons among various modelling approaches on the same platform [69]. In light of this, model-free approaches provide an alternative means to develop more complex yet accurate, design specific models without any prior knowledge about the underlying structure.

In terms of operating space, a closed loop configuration space controller or joint space controller would provide more stable and faster controllers, however cannot guarantee error convergence (Unless there is a perfect forward model available). Closed loop task space controllers can theoretically provide the best accuracy. In terms of actuation, tendon driven systems are more difficult to model, whereas pneumatic manipulators would need more sensors.

4. Model-Free Static Controllers

Model-free based approaches for control of continuum/soft robots is a relatively new field and offers a wide range of possibilities. Although, these data dependent methods have been used effectively in the field of rigid manipulators [72], the same cannot be said for continuum manipulators even though model-free approaches intuitively should fare better in this case.

The first usage of a model-free approach for development of a static controller was proposed in [32]. The approach was a straightforward direct learning of the inverse statics of a non-redundant (with respect to the actuator space and task space) soft robot using a neural network. Although the method was correctly able to predict the reference cable tensions for reaching a target in the task space in simulations, the approach cannot be scaled for redundant systems and does not consider the stochastic nature of real soft robots. An experimental validation of the same approach was done in [33] for a two DoF and a three DoF [34] cable driven soft manipulator and compared with an IK model derived from a numerically exact model. Interestingly, the simple neural network based approach performed significantly better than the computational complex analytical method. The final controller is similar to the diagram shown in Fig. 8 without the feedback component.

An efficient exploration algorithm for generating samples for IK learning was proposed in [35]. The main idea is to use goal babbling to generate samples from the task space to actuator space for high dimensional redundant systems. Since the exploration is goal oriented, it can allow for efficient exploration (by avoiding revisiting an explored task space/actuator space region) and in selecting a desired redundancy resolution scheme. Finally, self-organizing maps are used to learn the IK mapping with generated samples. A feedback scheme for reducing tracking error due to the stochasticity of model is implemented by virtually shifting the target positions proportional to the error in tracking to generate modified reference positions (Fig. 8).

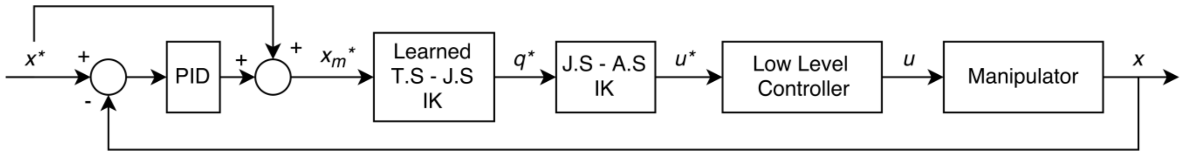

FIG. 8. A general model free closed loop task space controller implementation. A_m represents an auxiliary variable.

A highly robust, accurate and generic approach for closed loop task space control of continuum robots was proposed in [36] (Fig. 9). The paper proposes an optimal control strategy based on empirical estimation of the kinematic Jacobian matrix online by incrementally moving each actuator. Optimization is done to minimize the control effort and to keep the cables taut. There is no internal model used for control and therefore the authors have called the approach as a 'model-less' technique. Although such a strategy solves a lot of difficulties in the control of continuum robots, even allowing manipulation in an unstructured environment, the very low control frequency is of practical concern. The same principal was extended for hybrid force/position control in [37], where the stiffness matrix is also computed empirically. Similar to other hybrid force/position controllers, the reference position and forces are projected orthogonally when the manipulator is in contact.

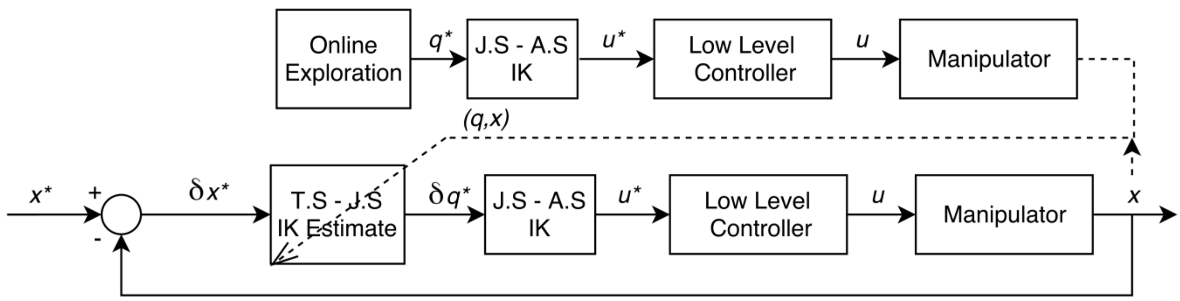

FIG. 9. Model-less control strategy.

Recent model free approaches have mostly focused on learning the IK representation of continuum robots. In [38], an approach for learning the direct mapping between task space and joint space (potentiometer voltage, in this case) is proposed. This involves learning the forward kinematic model first using a neural network and then inverting this learned network using Distal Supervised Learning. However, this approach did not consider the stochasticity of the manipulator and did not implement a feedback error correction scheme. As an improvement of the previous work, in [39], the authors try to address the stochasticity of the mapping between the joint space (potentiometer values) and actuator space (chamber pressures) by developing an adaptive sub-controller. This is because for the case of tendon-driven actuation, the actuator space and joint space are linearly related, whereas, for pneumatic actuation an additional non-linear mapping between the actuator space and the joint space must also be considered. The sub-controller comprises of a Modified Elman Neural Network which emulates the actuator kinematics and a Multilayer Perceptron controller that learns to control the actuator variables accordingly. However, the kinematic mapping between the joint space and task space is considered to be non-stochastic which is not necessarily the case. Another technique for learning the IK was proposed in [40, 41], where the IK problem is formulated like a differential IK problem using local mappings. This allowed for redundancy resolution as well as reducing stochastic effects. However, the approach was validated only by simulations on a continuum [40] and soft arm [41]. Another advantage of such an approach is that it allows multiple solutions to the IK problem globally and can work even if some of the actuators are nonfunctional after the learning process. A similar modelling method strengthened with a feedback controller was experimentally validated in [68]. It was also observed that even with a simple feedback controller, intelligent behaviors can be obtained in an unstructured environment.

An attempt towards transfer learning has also been made, however, limited to simulation [42]. Authors develop an algorithm to transfer the reaching skills from a simulated non-CC octopus arm to a simulated CC soft robotic manipulator. The idea is to design dynamic motion primitives through a weighted combination of Gaussian functions representing the joint distribution of the data. This is combined with a statistical regression approach making it robust to external perturbations in the environment. Although this approach seems promising, it requires more experimental work to demonstrate its potential. In a recent work [76], the authors optimize multiple objectives within a reinforcement learning architecture to learn deterministic stationary policies for a soft robot arm module. Although it works in high-dimensions, it is sensitive to external disturbances. An attempt towards fuzzy logic based controllers was attempted in [43]. The idea was to develop numerical estimates of the kinematic Jacobian using prior knowledge based local approximations and interpolation functions. This allows for faster computation, but the advantage of such a method over data driven machine learning approaches is not apparent. Finally, hybrid controller combining both model based and model free approach was proposed in [44], [74] and [75]. In [44], the manipulator is modelled as multiple sections with one translational and two rotational degrees of freedom. Then, multiple neural networks are used to resolve redundancy and to obtain the mapping from the task space to the high dimension configuration space. The configuration space to actuator space mapping is done analytically as it was found to be more straightforward. A noticeable limitation of such a method is the high sensory information required, which in the paper, the authors have synthesized from certain empirical data. A polar method was adopted in [74] with the configuration space to task space mapping being analytically modelled using the PCC approximation. The actuator space to configuration space mapping is learned also considering possible first order viscoelastic effects. A feedback strategy like in [35] was also employed to provide high tracking accuracy however only for a planar manipulator. In [75], it was shown that by learning only the model error incurred by an analytical model (a CC model), better forward and inverse kinematic models could be obtained. In this way it is also possible to leverage the advantages of an analytical model (like null space motions) along with the generality of learning methods.

4.1 Summary of Model-Free Static Controllers

One of the primary advantages of model-free approaches is to circumvent the need to define the parameters of the configuration space and/or joint space and is independent of the manipulator shape. Due to this, arbitrarily complex kinematic models can be developed depending upon the abundance of the sample data and sensory noise. This is probably why model-free approaches have fared better for systems that are highly nonlinear, non-uniform [33], influenced by gravity [35,68], or act within unstructured environments where modelling is almost impossible [36]. However, for well-behaved compact manipulators in known environments, model-based controllers are still more accurate and reliable. Furthermore, due to their black box nature, stability analysis and convergence proofs are difficult to establish.Static/kinematic controllers assume little or no dynamic coupling between sections.

As mentioned in the beginning, static/kinematic controllers rely on the steady state assumption, which hinders accurate and fast motion of soft manipulators. Hence, controllers that consider the dynamic behavior of these manipulators are important for faster, dexterous, efficient, smoother tracking and in situations where coupling effects cannot be ignored.

5. Model-Based Dynamic Controllers

Probably the most challenging field in the control of continuum/soft robots is the development of non-static controllers that considers the complete dynamics of the whole manipulator. Development of dynamic controllers would require the formulation of the kinematic model and an associated dynamic formulation. The fact that kinematic models are difficult to develop themselves; a dynamic formulation based on these imprecise models aggravates the model uncertainties [45]. On the other hand, even if exact kinematic and dynamic models are available, an appropriate controller would then require high dimensional sensory feedback [46]. Moreover, some dynamic properties/disturbances are inherently uncontrollable due to their under-actuated nature [47]. Development of reliable parameter estimation algorithms and accurate sensory information is also crucial.

One of the first theoretical studies on the dynamic control of continuum robots was done in [48]. In [48], it was validated through simulations of a planar single multi-section continuum robot that a simple feedforward and feedback PD controller can achieve exponential tracking of a set point. The feedforward component inputs the actuator torques that satisfies the static holding torques and the feedback component ensures the convergence of the set point position. A similar experimental study showed that a simple proportional controller can regulate the orientation of a planar continuum robot and a PD controller with coupling compensation can damp out manipulator vibrations [47]. Nonetheless, these studies were conducted on simplified models which do not capture the true nonlinearities of continuum/soft robots.

The first closed loop task space dynamic controller for continuum robots was demonstrated in [49], although, only by simulations. The kinematic for the two dimensional multi-section robot was formulated using the CC model and the corresponding dynamic model in the configuration was presented in the Euler-Lagrangian form using lumped dynamic parameters. One main difference of such a model from the dynamic model of a rigid robot is the addition of the potential energy due to bending and extension (dependent only on the kinematic configuration). In this dynamic equation the task space state variables can be substituted in place of the configuration state variables using the kinematic model. Note that by this way small errors in the kinematic model will exponentially rise when computing the higher order states and thereby affects the accuracy of dynamic model. The implemented controller can be described as a PD computed torque controller where the auxiliary control signal is represented in terms of the task space variables. An additional term for controlling the configuration space in the null space is also added. Although the robustness of the controller is shown by adding Gaussian white noise, the performance of such a controller can only be validated experimentally since it hinges on the CC approximation. However, the validity of the CC model for the same model was concurrently questioned in [45]. Furthermore, it must be bought to the attention of the reader that the stability proof was derived assuming that the kinematic and dynamic model is perfect. A different control approach for the same kinematic and dynamic model, in simulation, was done using a sliding mode controller in [50], however, only for closed loop configuration space control. A first order (assuming that the input output relative degree is two) sliding surface is defined as the filtered tracking error for this purpose. The advantage of a sliding mode controller over a simple inverse dynamics based PD controller is the higher robustness to model uncertainties; the downside being the slower error convergence, chattering and higher gain requirements. An experimental evaluation of this method was conducted with a planar three section continuum arm in [51], along with comparisons to a simple feedback linearization based PD controller in the configuration space. It was observed that the sliding mode controller performed better in terms of accuracy and speed indicating that model uncertainties were significant. Additionally, a task space controller for teleoperation was demonstrated using the controller mentioned in [49], which showed good tracking performance for a low frequency reference.

Considering the fact that the actuator dynamics of pneumatic actuators are slower and more nonlinear than tendon driven actuators, works focusing on optimal dynamic controllers for pneumatically actuated manipulators started to emerge. One such approach for trajectory optimization was demonstrated using simulations in [52], where the objective was to estimate the optimal trajectory that reduces the transition time and actuator jerk. The nonlinear optimization problem is formulated with kinematic constraints (CC model), actuator dynamic constraints and boundary constraints with the mass flow as the trajectory variable. Along the same lines, a trajectory optimization scheme for a comprehensive dynamic model of a soft planar manipulator was described in [53] (Fig. 10). Using the CC model for expressing the kinematics of the manipulator, a dynamic model was derived in the configuration space. A detailed derivation for calculating the generalized torques from the cylinder displacement and reference input is described in the paper. A direct collocation approach is employed to simultaneously identify the optimal generalized torques and corresponding manipulator state with the systems kinematics, dynamics, boundary conditions and tracking objective as constraints. The objective function is to reduce the final end effector velocity. An optimization problem is used for obtaining the optimal reference inputs to the actuator to realize the initial trajectory. Another advantage of a solving the control problem as an optimization problem is that it alleviates the need for a high level path planner. The open loop policy was successfully able to reach statically unreachable target points with high probability; the first demonstration in the field of continuum/soft manipulators. Even then an iterative learning control scheme to re-identify the system parameters was required in between trials for best performance.

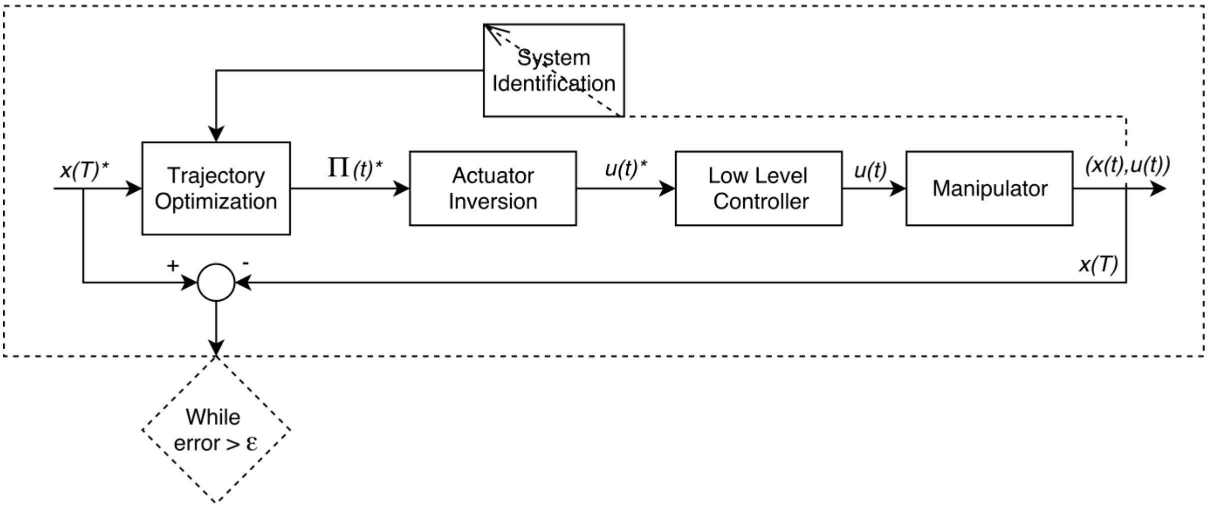

FIG. 10. Trajectory optimization algorithm for open loop dynamic task space control.

Another comprehensive model-based controller, seemingly a variation of [49], based on the dynamics of the joint space was proposed in [54]. The kinematics is based on the CC model and the dynamic model is represented in the joint space. A PD computed torque controller in the joint space is proposed. In order to transform the generalized torques used in the dynamic model to the desired actuator pressures', an inversion scheme is proposed. Experimental results even without the PD term showed decent results, validating the dynamic model. An extension of [54], which also considers the dynamics of the pneumatic chambers, was proposed in [55] (Fig. 11). With this, an inner loop decoupled PD computed torque controller is cascaded to the existing controller. Consideration of the pneumatic dynamics is important because its response is slower and more nonlinear compared to the dynamics of electromagnetic actuators. Since the controller does not consider the actuator and kinematic constraints, the performance is currently limited.

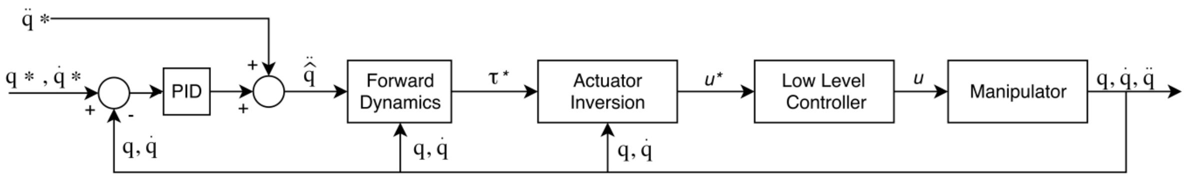

FIG. 11. Joint space dynamic controller by feedback linearization.

A recent interesting approach in the field of soft robotic manipulators in terms of design and control was stated in [56]. This soft humanoid robot was constructed such that the joints are similar to traditional rotational joints. Therefore, the kinematics of the manipulator can be modeled like traditional rigid robots allowing for much simpler dynamics models, which are identified empirically. The authors have ignored gravitational and cross coupling effects and the relationship between joint torques and pressure is derived. Due to the simplified model and design, a model predictive controller (MPC) in the joint space could be implemented at high frequency (300 Hz).

5.1 Summary of Model-Based Dynamic Controllers

Dynamic controllers are important for industrial applications where time and cost is also important along with the accuracy. Model based dynamic controllers for continuum/soft manipulators are still in their nascent stage, and consequently, there are a multitude of gaps that should be addressed in design, modelling, and control. Dynamic models directly mapping the control inputs (voltage, pressure or encoder values) to the task space variables should provide the ideal performance for any model based control approach. Currently, most of the dynamic control approaches are focused on the joint space control with an exception of few [53]. Even in this case, due to the computational complexity, the controller had to be designed in open-loop for a planar uniform manipulator. However, if the feedforward controller is perfect, this would be the most ideal choice. MPCs are ideal candidates for control of these continuum/soft manipulators, allowing for low gain accurate control. Their application is currently limited only because of the computational complexity of the current dynamic models.

With the increase in computational power, sensing capabilities and intelligent controllers, we can expect better developments in model based dynamic controllers. Alternatively, another route to consider are machine learning based approaches, either for learning open loop controllers, for dynamic compensation or for learning black box dynamic models.

6. Model-Free Dynamic Controllers

Model-free approaches for dynamic control of continuum/soft manipulators are still a relatively unexplored area. Nonetheless, the earliest usage of machine learning techniques for control of continuum robots was implemented for compensating for dynamic uncertainties in [57] (Fig. 12). However, the methodology was described only for closed loop dynamic control of the joint variables. The control architecture is composed of a feedback component which is based on a continuous asymptotic tracking control strategy for uncertain nonlinear systems (similar to a second order sliding mode controller) [58] and a feedforward component made using neural networks. The objective of the neural network is to compensate for the dynamic uncertainties and thereby reducing the uncertainty bound that improves the performance of the feedback controller.

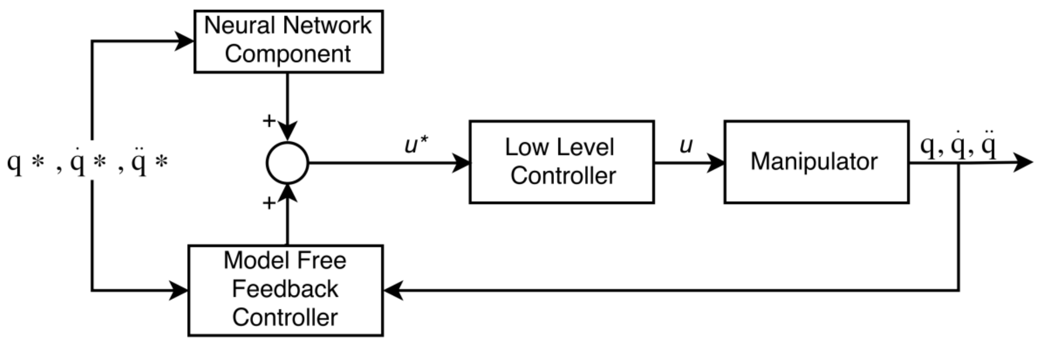

FIG. 12. Model-Free dynamic controller in the joint space.

In the domain of reinforcement learning, a simulated multi-segmented dynamical planar model of the octopus arm was developed in [59]. The authors then addressed the task of reaching a point by modelling the problem as a Hidden Markov Model that was solved online through a non-parametric Gaussian temporal difference learning algorithm. The underlying idea is to learn an action-value function via Bayesian inference from which an optimal control policy can be derived. In [60] it was demonstrated that an actor-critic based reinforcement learning approach could solve the same problem in the context of continuous action-spaces. A significant challenge, however, remains to adopt such methods in practice is to reduce the real-time costs for generating solutions.

Recently, the first direct actuator space to task space dynamic controller was experimentally demonstrated on a 3D soft pneumatic manipulator [71]. The approach involved learning the forward dynamic model using a class of recurrent neural network and employing trajectory optimization on the learned model just like [53]. Such types of controllers reveal a different region of dynamic behavior that a soft manipulator can attain in terms of speed, workspace volume and efficiency. The advantages of a model free approach are clearly evident in terms of the ease of modelling, accuracy and low sensory requirements. However, the controller is purely open loop due to the computational complexity and it was experimentally validated only on a single section manipulator.

6.1 Summary of Model-Free Dynamic Controllers

To sum up, although model-free approaches offer a relatively simpler path for developing dynamic controllers, practical applications are limited either due to training time or stability concerns [61]. Nonetheless, it is a possibility that should be looked upon, especially with the growth of more robust algorithms for training recurrent dynamic network [62]. That being said, hybrid controllers that merge model-based and model-free approaches could also be a viable approach to consider.

Table 1. Comparison of the state of the art control strategies presented in this paper

			Publication	Platform Details													Controller Details					
			Author and Year	Name	Type	No of Actuators	Actuator Shape	Actuator Spacing	No. of Segments	Segment Shape	Backbone	Body Material	Manipulator Shape	Functionalities	Payload	Intended Application	Planar / Non-Planar	Sensors^^	Performance	Theoretical Error Convergence: Configuration Space	Theoretical Error Convergence: Task Space	Stability
Model-Based	Tendon-Driven	Kinematic	P. Qi et al (2016)	N/A	C	3	Uniform	120°	1	Uniform	Multiple	3D printed	Uniform	B,C	N/A	Medical	Non-planar	Electromagnetic	Cartesian Error for Task Space Tracking			L-norm Stable
			Till et. al (2015)	N/A	C	6	Uniform	Tendon pairs at 120°	1	Uniform	-	Sring Steel, Acrylic Base	Uniform	B	N/A	Teleoperation	Non-planar	N/A	Mean run-time (ms)			N/A
			F. Largilliere et. al (2015)	N/A	S	4	Bow	90°	1	Uniform	-	Silicone	Uniform	B, C	N/A	N/A	Non-planar	Vision	Cartesian Error for Task Space Tracking (1.82mm)	No	Yes	N/A
			A. Bajo et. al (2015)	N/A	C	3	Uniform	120°	1	Uniform	Multiple	3D printed	Uniform	B,C	N/A	Medical	Non-planar	In-line load cell	Stiffness Map***	Yes	Yes	Asymptotic
			M. Giorelli et. al (2015)	Octopus	S	2	Uniform	180°	1	Tapering	-	Silicone	Tapering	B	N/A	Marine	Planar	In-line load cell / Vision	Cartesian Error for Set-Point Control (mean 7.35mm)	No	No	N/A
			W. Heshing et.al (2013)	Octopus	S	4	Uniform	90°	1	Tapering	-	Silicone	Tapering	B	N/A	Marine	Non-planar	Vision	Pixels Error for Set-Point Control (0)	No	Yes	Asymptotic
			R. S. Penning et. al (2012)	N/A	C	4	Uniform Uniform	90° 90°	1	Uniform Uniform	Teflon Teflon	Polyester mesh Polyester mesh	Uniform Uniform	B,C B,C	N/A	Medical Medical	Non-planar	Electromagnetic	Cartesian Error for Task Space Tracking, External Wrench Disturbance	No Yes	Yes No	N/A
			R. E. Goldman et. al (2011)	N/A	C	3	Uniform	120°	1	Uniform	Multiple	3D printed	Uniform	B,C	N/A	Medical	Planar	In-line load cell	Phase Lag, Orientation, External Wrench Rejection	Yes	N/A	Asymptotic
			A. Bajo et. al (2011)	N/A	C	3	Uniform	120°	3	Uniform	Multiple	3D printed	Uniform	B,C	N/A	Medical	Non-planar	Encoder and Magnetic	Phase Lag	Yes	N/A	Asymptotic
			DB Camarillo et. al (2009)	N/A	C	4	Uniform	90°	2	Uniform	Nitinol	Polyurethane	Uniform	B,C	N/A	Medical	Non-planar	Vision	Cartesian Error for Task Space Tracking (<1mm)	No	Yes	N/A
			DB Camarillo et. al (2009)	N/A	C	4	Uniform	90°	2	Uniform	Nitinol	Polyurethane	Uniform	B,C	N/A	Medical	Non-planar	Vision	Cartesian Error for Configuration Tracking, Tension, and Orientation	No	No	N/A
		Dynamic	-	-	-				-								-					
	Pneumatic	Kinematic	A.D. Marchese et. al (2015)	N/A	S	16	Anistropic Stiffness	90°	4	Uniform	-	Silicone	Tapering	B		NSS	Planar	Vision	Cartesian Error for Configuration Tracking, Curvature vs Time	Yes	No	N/A
			T Mahl et. al (2014)	Bionic Handling Assistant	C	9	Bellow	120°	3	Tapering	-	3D printed	Tapering	B,E	N/A	Industry	Non-planar	Vision	Cartesian Error for Open Loop Task Space Tracking	Yes	No	N/A
		Dynamic	V. Falkenhhn et. al (2016)	Bionic Handling Assistant	C	9	Bellow	120°	3	Tapering	-	3D printed	Tapering	B,E	N/A	Industry	Non-planar	Cable Potentiometer, Pressure Sensor	Cartesian Tracking Error, External Disturbance Rejection, Gravity Compensation	No	No	N/A
			A.D. Marchese et. al (2015)	N/A	S	16	Anistropic Stiffness	90°	4	Uniform		Silicone	Tapering	B		NSS	Planar	Vision	Velocity tracking error	No	No	N/A
			A. Kapadia (2014)	Octarm	S	3	Uniform	120°	3	Uniform	-	Mckibben	Tapering	B,E	0.9kg	Military	Planar	String Encoder to measure cable length	Cartesian Length / Curvature Plots Configuration Error Cartesian Length / Curvature Plots Configuration Error Carteisan Tracking Error	Yes Yes No	No No Yes	Asymptotic Asymptotic Asymptotic
			A. Kapadia (2011)*	Octarm	S	9	Uniform	120°	3	Uniform	-	Mckibben	Tapering	B,E	0.9kg	Military	Planar	-	Cartesian Error for Tip Position/Curvature Legnth Error Section Length/ Curvature Control Torque Error	Yes	No	Asymptotic
			A. Kapadia (2010)*	Octarm	S	9	Uniform	120°	3	Uniform	-	Mckibben	Tapering	B,E	0.9kg	Military	Planar	-	Cartesian Error for Section Length/Curve, Control Torque Error	No	No	Asymptotic
	Interleaved	Kinematic	C. Benjamin and M.Zinn (2015)*	N/A	C	2	Uniform	-	4		-	Serial concatenation of revolute and flexible joints	Uniform	B		NSS	Non-planar	-	Cartesian Error for Task Space Tracking	No	Yes	N/A
Model-Free	Tendon-Driven	Kinematic	M.C. Yip (2016)	N/A	C	2	Uniform	180°	1	Uniform	Multiple	3D printed	Uniform	B		Medical	Planar	Vision, In-line load cell, Multi-axis Force Sensor	Cartesian Error for Task Space Tracking, Tip Force vs Time	No	Yes	Asymptotic
			T. G. Thurutel et al (2017)	N/A	C	6	Uniform	120°	2	Uniform	-	Layer-by-layer	Uniform	B,C	N/A	N/A	Non-planar	Electromagnetic	Cartesian Error forTask Space Tracking	No	No	N/A
			M. Giorelli et.al (2015)	Octopus	S	2	Uniform	180°	1	Tapering	-	Silicone	Tapering	B	N/A	Marine	Planar	In-line load cell / Vision	Carteisan Error for Set Point Control	No	No	N/A
		Dynamic	-	-	-				-								-				-	
	Pneumatic	Kinematic	Jiang et. al (2017)	Honeycomb Pneumatic Network	S	20	Honeycomb shaped	-	5	Uniform	-	3D printed	Uniform	B,E	N/A	N/A	Planar	Vision	Cartesian Error in Task Space Tracking (less than 8mm)	No	No	N/A
			A. Melingui et. al (2015)	Compact Bionic Handling Assistant	C	9	Bellow	120°	3	Tapering		3D printed	Tapering	B,E	N/A	Industry	Non-planar			Yes	No	
			Rolf et. al (2013)	Bionic Handling Assistant	C	9	Bellow	120°	3	Tapering	-	3D printed	Tapering	B,E	N/A	Industry	Non-planar	Vision	Cartesian Error for Task Space Tracking (5mm)	No	Yes	N/A
		Dynamic	Thuruthel et. al (2017)	I-Support	C	3	Uniform	120°	1	Uniform	-	Layer-by-layer	Uniform	E, B	N/A	Assistive	Planar	Vision	Cartesian/Velocity/Acceleration Tracking Error	No	No	N/A
			D. Braganza (2007)	Octarm	S	9	Uniform	120°	3	Uniform	-	Polyester mesh	Tapering	E, B	0.9kg	Military	Non-planar	Encoders	Joint space error	No	No	Semi Global Asymptotic
	Octopus Arm Simulation	Kinematic	Malakzadeh et. all (2014)*	Octopus STIFF-FLOP	S	NSS 6	Uniform Uniform	Serial-links 120°	NSS 2	Tapering Uniform	- -	- -	Marine Uniform	B	N/A	Medical	Non-planar	-	Rotational and Translational Error in Task Space Tracking	No	No	Local Optimum
		Dynamic	Thuruthel et. al (2017)	Octopus	S	3	-	-	4	Tapering	-	-	Tapering	Reaching	N/A	N/A	Non-planar	-	Reaching Time and Reaching Error	No	No	N/A
			Guy Lever et. al(2014)*	Octopus	S	1	-	-	6	Tapering	-	-	Tapering	Reaching	N/A	N/A	Planar	-	Convergence Time for Set-Point Control, Success Rate	No	No	N/A
			Engel et. al(2014)*	Octopus	S	1	-	-	10	Tapering	-	-	Tapering	Reaching	N/A	N/A	Planar	-	Convergence Time for Set-Point Control	No	No	N/A
	Hybrid	Kinematic	Y. Ansari et al (2017)	I-Support	C	6	Tendon: Uniform Pneumatic: Bellow	60°	1	Uniform	-	Layer-by-layer	Uniform	B,E,C	N/A	Assistive	Non-planar	Electomagnetic	Cartesian Error	No	No	N/A
Hybrid	Tendon-Driven	Static	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		Dynamic	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Pneumatic	Static	Reinhart et al (2017)	Bionic Handling Assistant	C	9	Bellow	120°	3	Tapering	-	3D Printed	Tapering	B,E	N/A	Industry	Non-planar	Vision	Cartesian Error for Task Space Tracking	No	No	N/A
			O. Lakhal et. al (2016)	Compact Bionic Handling Assistant	C	9	Bellow	120°	3	Tapering	-	3D Printed	Tapering	B,E	N/A	Industry	Non-planar	Vision, Cable-Potentiometer	Cartesian Error for Task Space Tracking	No	No	N/A
		Dynamic	-	-	-				-								-				-	

* Simulation
** Not Specifically Mentioned
*** Requires Simultaneous measurement of Cartesian and Force Values
^^ Necessary for Controller - Feedback Sensorsnot included
C- Continuum; S - Soft

8. DISCUSSIONS

From our survey on the current control approaches in soft robotics, it is apparent that the design of controllers for continuum/soft manipulators is not only application dependent but also influenced by the manipulator design, actuator and sensor availability. Therefore it is difficult to compare and contrast all the approaches under the same umbrella. However, depending on the design, actuation and application there are some trends observed. Classification of a manipulator as continuum or soft did not affect the controller design; at least, it is not evident. This means that controllers developed for continuum manipulators can be easily transferred to their soft sub-group. Medical applications that rely on compact manipulators, manufactured with high precision, tend to employ model-based approaches because of its reliability and high controlled environment. Likewise, manipulators with non-uniform geometry and high nonlinearity tend to employ model-free methods for a lack of better analytic models. For manipulation in unstructured environments, currently only model-free methods have shown promising results

Another interesting observation is the absence of dynamic controllers developed for tendon-driven manipulators. This could be because of the non-uniform loading for cable actuation contrasting to the high damping and low force actuation provided by pneumatic actuators. Non-uniform loading occurs due to the physical interactions between the cable guide and the cable due to friction and this leads to irregular actuation of the manipulator DoFs. High damping coupled with low force actuation reduces overall energy supplied to the system therefore reducing the chaotic nature of the manipulator dynamics.

The controller regime to some extent depends on the sensor availability. For instance, closed-loop configuration space controllers require vision sensors. Model based closed loop kinematic controllers for pneumatically actuated manipulators used wire cable potentiometers. This is because joint space estimation for pneumatic actuation in not so straightforward like rigid robots.

With regards to unexplored fields of research, clear voids are evident in hybrid control approaches and model-free approaches for dynamic control. Application of machine learning for learning the dynamic mapping from the actuator space to task space/configuration space is a viable method to be investigated. Similarly, hybrid learning approaches incorporating both model-based and model-free methods is a highly promising line of research. Additionally, machine learning algorithms incorporating prior knowledge of the system would also provide a way for faster and more stable learning [63]. Another overlooked topic is the importance of the low level controllers (actuator dynamics) in the overall stability and response of the higher level control architecture.

Continuum/Soft manipulators offer a technological solution to complex tasks in sensitive environments. Leveraged by their light weight, compact and inherently safe structure, they can be employed in various complex scenarios with elementary control strategies [6, 7]. Current trends in soft robot are individual efforts based on novel actuation, design, sensing and control technologies for particular applications. However, an overlooked aspect is the interdependencies of these elements among themselves and with the environment [64]. The possibility of outsourcing computational burden to the body (morphological computation) has been widely deliberated and even experimentally proven [65] along with the effect of sensory feedback [66]. In a control perspective, this corresponds to a zero lag adaptive feedback controller. Exploitation of this intrinsic controller has been achieved in some cases [67]. We believe that the future evolution of controllers for soft robotic manipulators would also be in this direction, where the morphological properties of the complex manipulators would also be utilized for more accurate, robust and dexterous manipulation.

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